International Journal of Mechanical and Production Engineering Research and Development (IJMPERD)
ISSN(P): 2249-6890; ISSN(E): 2249-8001
Vol. 8, Issue 1, Feb 2018, 229-242

ANALYSIS OF FUZZY SOFT SET COMPOSITIONS FOR ALLOCATING JOBS TO MACHINES IN FUZZY ENVIRONMENT

C. KAVITHA[1], T. S. FRANK GLADSON[2] & C. M. ARUN KUMAR[3]

[1]*Department of Mathematics, Sathyabama University, Chennai*

[2]*Department of Mechanical, Velammal Engineering College, Surapet, Chennai*

[3]*Department of Electronics and Communication Engineering, University College of Engineering, Pattukkotai*

ABSTRACT

Real world situation often exist with high degree of uncertainty in decision making. In such situation, decision makers can use fuzzy soft set which is a mathematical tool for dealing with uncertainties and has rich potential for application in several directions. The aim of this paper is to calculate the uncertain degree of various parameters and to assign a particular job to a particular machine to get the desired optimization with the use of triangular fuzzy numbers. In the present study, four different cases for fuzzy soft set compositions are considered and compared to incorporate the uncertainty using fuzzy triangular numbers.

KEYWORDS: Triangular Fuzzy Number, Defuzzification & Fuzzy Soft Set

Received: Nov 14, 2017; **Accepted:** Dec 04, 2017; **Published:** Jan 05, 2018; **Paper Id.:** IJMPERDFEB201827

Original Article

1. INTRODUCTION

In real life situation, all the fields deal with complexity of modeling uncertain data. Classical methods such as probability theory, rough sets and other mathematical tools are not successful to deal the uncertain data. Molodstov [5] proposed a mathematical tool for modeling vagueness and uncertainty with basic notions of the theory of soft sets. Fuzzy soft set to solve a decision making problem using rough mathematics has been proposed [4]. In recent years, soft set and fuzzy soft set theories have been proved to be useful in many different fields, such as decision making [15,16]. Muhammad Irfan Ali et al. discussed some new operations in soft set theory and approximation space associated with each parameter in a soft set [6,7]. Yildiray celik [13] developed a technique to diagnose which patient is suffering from what disease. Palash dutta [8] proposed the concept of bell shaped fuzzy soft set and its application in medical diagnosis using arithmetic operations of discrete-gaussian fuzzy number, triangular-cauchy fuzzy number and Gaussian-cauchy fuzzy number. Kalaiselvi.s [3] apply the decision method which is based on sanchez's method to solve the job scheduling problem under uncertain information by using the notions of fuzzy soft set and fuzzy numbers. Chetia[1] extend sanchez's approach for medical diagnosis using interval-valued fuzzy soft sets. yildiray celik [14] introduce matrice representation of fuzzy soft sets. Degang chen et.al [2] propose parameterization reduction of soft sets and compare it with the concept of attributes reduction in rough sets theory. Neutrosophic logic has been proposed by Florentine smarandache [11,12] which is based on non-standard analysis that was given by Abraham Robinson in 1960s. Saikia et al [9] have extended the sanchez's method by using intuitionistic fuzzy soft set theory.

The objective of this paper is to deal the uncertain degree of various parameters in allocating jobs to machine such as machine breakdowns, processing times variations, cancellation or arrivals of new jobs and consumption cost etc to assign a particular job for a particular machine. We solve the uncertainty with the use of triangular fuzzy numbers in fuzzy soft set by the method analogues to sanchez's[10] method for diagnosis.

II. Preliminaries

We give here some basic definitions which are used in our next section.

Definition 2.1: Triangular Fuzzy Number Matrix

Triangular fuzzy number matrix of order m×n is defined as $A=\left(a_{ij}\right)_{m\times n}$ where $a_{ij}=\left(a_{ijL},a_{ijM},a_{ijU}\right)$ is the ij[th] element of A. a_{ijL},a_{ijU} are the left and right limit of a_{ij} respectively and a_{ijM} is the mean value.

Definition 2.2: Addition and Subtraction Operation of Triangular Fuzzy Number Matrix

Let A and B be two triangular fuzzy numbers parameterized by the triplet $b_1=\left(a_1,b_1,c_1\right)$ and $b_2=\left(a_2,b_2,c_2\right)$ respectively. Then addition and subtraction of A and B are

$$A\oplus B=\tilde{a}_2\oplus\tilde{b}_2$$

$$=\left(a_1,a_2,a_3\right)\oplus\left(b_1,b_2,b_3\right)=(a_1+b_1,a_2+b_2,\mathrm{a}_3+b_3)\text{ and}$$

$$A\,(-)\,B=\tilde{a}_2\,(-)\,\tilde{b}_2$$

$$=\left(a_1,a_2,a_3\right)(-)\left(b_1,b_2,b_3\right)=(a_1-b_3,a_2-b_2,\mathrm{a}_3-b_1)$$

Definition 2.3: Multiplication Operation on Triangular Fuzzy Number Matrix

Let $A=(a_{ij})_{m\times p}$ and $B=\left(b_{ij}\right)_{p\times n}$ be two triangular fuzzy number matrices. Then the multiplication operation

$$A(.)B=\left(c_{ij}\right)_{m\times n}\quad where\quad \left(\mathrm{c}_{\mathrm{ij}}\right)=\sum_{k=1}^{p}a_{ik}b_{kj}\quad\text{for i}=1,2\text{...m and j}=1,2\text{....n}$$

Definition 2.4: Maximum Operation on Triangular Fuzzy Number

Let $A=(a_{ij})_{n\times n}$ and $B=\left(b_{ij}\right)_{n\times n}$ where $\mathrm{a}_{\mathrm{ij}}=\left(a_{ijL},a_{ijM},a_{ijU}\right)$ and $B=\left(b_{ij}\right)_{n\times n}$ where $\mathrm{b}_{\mathrm{ij}}=\left(b_{ijL},b_{ijM},b_{ijU}\right)$ be two triangular fuzzy number matrices of same order. Then the maximum operation on it is given by $L_{\max}=\max(A,B)=\sup\{a_{ij},b_{ij}\}$ where $\sup\{a_{ij},b_{ij}\}=\left(\sup\left(a_{ijL},b_{ijL}\right),\sup\left(a_{ijM},b_{ijM}\right),\sup\left(a_{ijU},b_{ijU}\right)\right)$ is the ij[th] element of max (A, B).

Definition 2.5: Max-Min Composition on Fuzzy Membership Value Matrices

Let F_{mn} denote the set of all $m\times n$ matrices over F. Elements of F_{mn} are called as fuzzy membership value

matrices. For $A=(a_{ij})\in F_{mp}$ and $B=(b_{ij})\in F_{pn}$ the max-min product $A(.)B=(\sup_k\{\{\inf\{a_{ik},b_{kj}\}\}\})\in F_{mn}$

Definition 2.6: Triangular Fuzzy Number

A fuzzy number is a fuzzy set defined on the universe of discourse X which is both convex and normal. A fuzzy number μ on the universe of discourse X may be characterized by a triangular fuzzy number which is parameterized by a triplet $\tilde{b}=(a,b,c)$. The membership function of this fuzzy number is defined as

$$\mu_A(x)=\begin{cases}0 & for \quad x \prec a\\ \dfrac{x-a}{b-a} & for \quad \mathrm{a} \le \mathrm{x} \le \mathrm{b}\\ \dfrac{\mathrm{c-x}}{\mathrm{c-b}} & for \quad \mathrm{b} \le \mathrm{x} \le \mathrm{c}\\ 1 & for \quad \mathrm{x} \succ \mathrm{c}\end{cases}$$

Definition 2.7: Defuzzification For Triangular Fuzzy Number

Defuzzification for the triangular fuzzy number $\tilde{b}=(a,b,c)$ is the centroid of $\tilde{b}$ is $\mathrm{C}_{\tilde{b}}=\dfrac{a+b+c}{3}$

Definition 2.8: Soft Set

Let U be an initial universe set and E be a set of parameters. The power set of U is denoted by P(U) and A is a subset of E. A pair (F, A) is called a soft set over U, where F is a mapping given by F: A $\longrightarrow$P(U)

Definition 2.9: Fuzzy Soft Set

Let U be a common universe, E be a set of parameters and $A\subseteq E$. Then a pair $(\tilde{F},A)$ is called a fuzzy soft set over U, where $\tilde{F}$ is a mapping given by $\tilde{F}:A\longrightarrow\Im(U)$

Definition 2.10: Union and Intersection of Fuzzy Soft Set

The union and intersection of the relations $\tilde{T}_1$ and $\tilde{T}_2$ of the fuzzy soft set (F,A) and (G, B) over a common universe U respectively is defined as

$$(\tilde{T}_1\cup\tilde{T}_2)(a,b)=\max(\tilde{T}_1(a,b),\tilde{T}_2(a,b))$$

$$(\tilde{T}_1\cap\tilde{T}_2)(a,b)=\min(\tilde{T}_1(a,b),\tilde{T}_2(a,b))$$

Definition 2.11: Max-Avg-Min Composition

Let A be a fuzzy soft set in X. Let R be the relation from X to Y and Let B be a fuzzy soft set in Y. Let R be the relation from Y to Z. Then max-avg-min composition of fuzzy soft set with A is another fuzzy soft set B is $A^\circ B=\{(x_i,z_k)/L_{A\circ B}(x_i,z_k),M_{A\circ B}(x_i,z_k),R_{A\circ B}(x_i,z_k)$. Then the membership function of B is defined as

$$L_{A\circ B}(x_i,z_k)=\vee_x\left[L_A(x_i,y_j)\wedge L_B(y_j,z_k)\right],$$

$$M_{A\circ B}(x_i,z_k)=\vee_x\left[\frac{1}{2}[M_A(x_i,y_j)+M_B(y_j,z_k)]\right],$$

$$R_{A\circ B}(x_i,z_k)=\wedge_x\left[R_A(x_i,y_j)\vee R_B(y_j,z_k)\right]$$

Definition 2.12: Max-Prod-Min Composition

Let A be a fuzzy soft set in X. Let R be the relation from X to Y and Let B be a fuzzy soft set in Y. Let R be the relation from Y to Z. Then max-prod-min composition of fuzzy soft set with A is another fuzzy soft set B is $A^{\circ}B=\{(x_i,z_k)/L_{A\circ B}(x_i,z_k),M_{A\circ B}(x_i,z_k),R_{A\circ B}(x_i,z_k)$. Then the membership function of B is defined as

$$L_{A\circ B}(x_i,z_k)=\vee_x\left[L_A(x_i,y_j)\wedge L_B(y_j,z_k)\right],$$

$$M_{A\circ B}(x_i,z_k)=\vee_x\left[M_A(x_i,y_j)*M_B(y_j,z_k)\right],$$

$$R_{A\circ B}(x_i,z_k)=\wedge_x\left[R_A(x_i,y_j)\vee R_B(y_j,z_k)\right]$$

Definition 2.13: Max-Max-Min Composition

Let A be a fuzzy soft set in X. Let R be the relation from X to Y and Let B be a fuzzy soft set in Y. Let R be the relation from Y to Z. Then max-prod-min composition of fuzzy soft set with A is another fuzzy soft set B is $A^{\circ}B=\{(x_i,z_k)/L_{A\circ B}(x_i,z_k),M_{A\circ B}(x_i,z_k),R_{A\circ B}(x_i,z_k)$. Then the membership function of B is defined as

$$L_{A\circ B}(x_i,z_k)=\vee_x\left[L_A(x_i,y_j)\wedge L_B(y_j,z_k)\right],$$

$$M_{A\circ B}(x_i,z_k)=\vee_x\left[M_A(x_i,y_j)\wedge M_B(y_j,z_k)\right],$$

$$R_{A\circ B}(x_i,z_k)=\wedge_x\left[R_A(x_i,y_j)\vee R_B(y_j,z_k)\right]$$

Definition 2.14: Max-Min-Max Composition

Let A be a fuzzy soft set in X. Let R be the relation from X to Y and Let B be a fuzzy soft set in Y. Let R be the relation from Y to Z. Then max-prod-min composition of fuzzy soft set with A is another fuzzy soft set B is $A^{\circ}B=\{(x_i,z_k)/L_{A\circ B}(x_i,z_k),M_{A\circ B}(x_i,z_k),R_{A\circ B}(x_i,z_k)$. Then the membership function of B is defined as

$$L_{A\circ B}(x_i,z_k)=\vee_x\left[L_A(x_i,y_j)\wedge L_B(y_j,z_k)\right],$$

$$M_{A\circ B}(x_i,z_k)=\wedge_x\left[M_A(x_i,y_j)\vee M_B(y_j,z_k)\right],$$

$$R_{A\circ B}(x_i,z_k)=\vee_x\left[R_A(x_i,y_j)\wedge R_B(y_j,z_k)\right]$$

Definition 2.15: Scores of Fuzzy Soft Set

Let (F, A) be fuzzy soft set. Then the score function of (F, A) is defined as

(i) $S_k^1 = L_k - R_k M_k$

(ii) $S_k^2 = L_k - \left(\frac{R_k + M_k}{2} \right)$

(iii) $S_k^3 = \left(\frac{L_k + R_k}{2} \right) - M_k$

(iv) $S_k^4 = \left(\frac{L_k + M_k}{2} \right) - R_k$

(v) $S_k^1 = (L_k * M_k) - R_k$

3. METHODOLOGY

In this section, we compare four types of fuzzy soft set relation for allocating jobs to machines under uncertain information [3] using fuzzy triangular numbers.

Algorithm: 1

Step 1

Suppose there are a set of *m* jobs, $J = \{j_1, j_{2,......} j_m\}$ with a set of *n* criteria's $C = \{c_1, c_{2,......} c_n\}$ under uncertain situation related to a set of *k* machines $M = \{m_1, m_{2,......} m_k\}$. Construct a fuzzy soft set (F, J) over C where F is a mapping $F: J \to \tilde{F}(C)$ where $\tilde{F}(C)$ is a set of all triangular fuzzy sets of C. Input this fuzzy soft set which gives a relation matrix (weighted matrix) P, called job-attribute (criteria) matrix, where each element denotes the weight of the job related to the level of attribute and are noted in table 1. Here the elements in the relation matrix are taken as triangular fuzzy number $\tilde{p}$ parameterized by the triplet (p-1, p, p+1) where p-1 and p+1 are the left and right spreads of p respectively

Step 2

Similarly construct another fuzzy soft set (G, C) over m, where G is a mapping $G: C \to \tilde{F}(M)$ where $\tilde{F}(M)$ is a set of all triangular fuzzy sets of M. Input this fuzzy soft set which gives a relation matrix (weighted matrix) Q called attribute-machine matrix, where each element denote the weight of the level of attribute for a particular machine and are noted in table 2.

Step 3

Perform the transformation operation T= $P \otimes Q$ to know the relation of jobs with respect to the machines, to get the job assignment matrix using the definition [2.11] and is noted in table 3.

Step 4: The score function for the values in table 3 is found using definition 2.7, 2.15 and it is given in table 4-9.

Step 5: Find the higher score for possibility of the job related with the respective machines.

Step 6: Final decision is based on the majority vote obtained in all the scores.

Algorithm: 2

Step 1and Step 2 is same as Algorithm 1

Step 3:

Perform the transformation operation T= $P \otimes Q$ to know the relation of jobs with respect to the machines, to get the job assignment matrix using the definition [2.12] and is noted in table 10.

Step 4: The score function for the values in table 10 is found using definition 2.7, 2.15 and it is given table 11 –16.

Step 5and **Step 6** is same as Algorithm 1

Algorithm: 3

Step 1and **Step 2** is same as Algorithm 1

Step 3:

Perform the transformation operation T= $P \otimes Q$ to know the relation of jobs with respect to the machines, to get the job assignment matrix using the definition [2.13] and is noted in table 17.

Step 4: The score function for the values in Table 17 is found using definition 2.7, 2.15 and it is given table 18 –23.

Step 5and **Step 6** is same as Algorithm 1.

Algorithm: 4

Step 1and **Step 2** is same as Algorithm 1

Step 3:

Perform the transformation operation T= $P \otimes Q$ to know the relation of jobs with respect to the machines, to get the job assignment matrix using the definition [2.14] and is noted in table 24.

Step 4: The score function for the values in Table 17 is found using definition 2.7, 2.15 and it is given table 25-30.

Step 5and **Step 6** is same as Algorithm 1

4. CASE STUDY

Suppose that a manufacturing company has to manufacture a product. It needs four jobs to process in four different machines with three criteria's which cannot be specified precisely or accurately due to the error of the measuring technique etc. It is defined as $J = \{j_1, j_{2,} j_3, j_4\}$ as four jobs, set of four machines as $M = \{m_1, m_{2,} m_3, m_4\}$ with three criteria as $C = \{c_1, c_{2,} c_3\}$ named as processing time, number of labors needed, total expenses in uncertain situation. To identify the machine this is suitable for that particular job in a quick manner, we compare four different compositions in fuzzy soft set.

Case I:

Suppose that $F : J \to \tilde{F}(C)$ is defined as

$$F(j_1) = \{c_1 /(0.6,0.7,0.8), c_2 /(0.0,0.1,0.2), c_3 /(0.7,0.8,0.9)\},$$

$$F(j_2) = \{c_1 /(0.2,0.3,0.4), c_2 /(0.8,0.9,1.0), c_3 /(0.1,0.2,0.3)\}$$

$F(j_3)=\{c_1/(0.8,0.9,1.0), c_2/(0.1,0.2,0.3), c_3/(0.5,0.6,0.7)\}$

$F(j_4)=\{c_1/(0.0,0.1,0.2), c_2/(0.1,0.2,0.3), c_3/(0.7,0.8,0.9)\}$.

Then the fuzzy soft set (F, J) is a parameterized family of all fuzzy sets over C. This fuzzy soft set (F, J) represents the relation matrix, job-attribute matrix P and is given in table 1.

Table 1: Job-Criteria Matrix P

P	Processing time(C1)	Number of labors needed(C2)	Total expenses(C3)
Job1(J1)	(0.6,0.7,0.8)	(0.0,0.1,0.2)	(0.7,0.8,0.9)
Job2(J2)	(0.2,0.3,0.4)	(0.8,0.9,1.0)	(0.1,0.2,0.3)
Job3(J3)	(0.8,0.9,1.0)	(0.1,0.2,0.3)	(0.5,0.6,0.7)
Job4(J4)	(0.0,0.1,0.2)	(0.1,0.2,0.3)	(0.7,0.8,0.9)

Next suppose that $G: C \to \tilde{F}(M)$ is defined as

$G(c_1)=\{m_1/(0.0,0.1,0.2), m_2/(0.2,0.3,0.4), m_3/(0.4,0.5,0.6), m_4/(0.3,0.4,0.5)\}$

$G(c_2)=\{m_1/(0.3,0.4,0.5), m_2/(0.5,0.6,0.7), m_3/(0.6,0.7,0.8), m_4/(0.7,0.8,0.9)\}$

$G(c_3)=\{m_1/(0.5,0.6,0.7), m_2/(0.4,0.5,0.6), m_3/(0.2,0.3,0.4), m_4/(0.1,0.2,0.3)\}$

Then the fuzzy soft set (G, C) is a parameterized family of all fuzzy sets over M. This fuzzy soft set (G, C) represents the relation matrix, attribute-machine matrix Q and is given in table 2.

Table 2: Criteria-Machine Matrix Q

Q	Machine1(M1)	Machine2(M2)	Machine3(M3)	Machine4(M4)
Processing time(C1)	(0.0,0.1,0.2)	(0.2,0.3,0.4)	(0.4,0.5,0.6)	(0.3,0.4,0.5)
Number of labors needed(C2)	(0.3,0.4,0.5)	(0.5,0.6,0.7)	(0.6,0.7,0.8)	(0.7,0.8,0.9)
Total expenses(C3)	(0.5,0.6,0.7)	(0.4,0.5,0.6)	(0.2,0.3,0.4)	(0.1,0.2,0.3)

When the input matrixes are given, perform the transformation operation $P \otimes Q$ to get the job assignment matrix T. It is calculated using max-avg-min composition and is given in table 3.

Table 3: Job Assignment Matrix Using Max-Avg-Min Composition

T	Machine1(M1)	Machine2(M2)	Machine3(M3)	Machine4(M4)
Job(J1)	(0.5,0.7,0.5)	(0.4,0.65,0.7)	(0.4,0.6,0.8)	(0.3,0.55,0.8)
Job(J2)	(0.3,0.65,0.4)	(0.5,0.75,0.4)	(0.6,0.8,0.4)	(0.7,0.85,0.3)
Job(J3)	(0.5,0.6,0.5)	(0.4,0.6,0.7)	(0.4,0.7,0.7)	(0.3,0.65,0.7)
Job(J4)	(0.5,0.7,0.2)	(0.4,0.65,0.4)	(0.2,0.55,0.6)	(0.1,0.5,0.5)

Score values for the table 3 is calculated in table 4-9 using definition 2.7 and 2.15.

Table 4: Score Value Using Defn 2.7

	M1	M2	M3	M4
J1	0.57	0.58	**0.6**	0.55
J2	0.45	0.55	0.6	**0.62**
J3	0.53	0.57	**0.6**	0.55
J4	0.47	**0.48**	0.45	0.37

Table 5: Score Value for S_k^1

S_1	M1	M2	M3	M4
J1	**0.15**	-0.055	-0.08	-0.14
J2	0.04	0.2	0.28	**0.445**
J3	**0.2**	-0.02	-0.09	-0.155
J4	**0.36**	0.14	-0.13	-0.15

Table 6: Score Value for S_k^2

S_2	M1	M2	M3	M4
J1	**-0.1**	-0.275	-0.3	-0.375
J2	-0.225	-0.075	0	**0.125**
J3	**-0.05**	-0.25	-0.3	-0.375
J4	**0.05**	-0.125	-0.375	-0.4

Table 7: Score value for S_k^3

S_3	M1	M2	M3	M4
J1	-0.2	-0.1	**0**	**0**
J2	**-0.3**	**-0.3**	**-0.3**	-0.35
J3	-0.1	**-0.05**	-0.15	-0.15
J4	-0.35	-0.25	**-0.15**	-0.2

Table 8: Score Value for S_k^4

S_4	M1	M2	M3	M4
J1	**0.1**	-0.175	-0.3	-0.375
J2	0.075	0.225	0.3	**0.475**
J3	**0.05**	-0.2	-0.15	-0.225
J4	**0.4**	0.125	-0.225	-0.2

Table 9: Score Value For S_k^5

S_5	M1	M2	M3	M4
J1	**-0.15**	-0.44	-0.56	-0.635
J2	-0.205	-0.025	0.08	**0.295**
J3	**-0.2**	-0.46	-0.42	-0.505
J4	**0.15**	-0.14	-0.49	-0.45

Case II

Step 1 and Step 2 are same as Case I

When the input matrixes are given, perform the transformation operation $P \otimes Q$ to get the job assignment matrix T. It is calculated using max-prod-min composition and is given in table 10.

Table 10: Job Assignment Matrix Using Max-Prod-Min Composition

T	Machine1(M1)	Machine2(M2)	Machine3(M3)	Machine4(M4)
Job(J1)	(0.5,0.48,0.5)	(0.4,0.40,0.7)	(0.4,0.35,0.8)	(0.3,0.28,0.8)
Job(J2)	(0.3,0.36,0.4)	(0.5,0.54,0.4)	(0.6,0.63,0.4)	(0.7,0.72,0.3)
Job(J3)	(0.5,0.36,0.5)	(0.4,0.3,0.7)	(0.4,0.45,0.7)	(0.3,0.36,0.7)
Job(J4)	(0.5,0.48,0.2)	(0.4,0.4,0.4)	(0.2,0.24,0.6)	(0.1,0.16,0.5)

Score values for the table 10 is calculated in table 11-16 using definition 2.7 and 2.15.

Table 11: Score Value Using Defn 2.7

	M1	M2	M3	M4
J1	0.49	0.5	**0.52**	0.46
J2	0.35	0.48	0.54	**0.57**
J3	0.45	0.47	**0.52**	0.45
J4	0.39	**0.4**	0.35	0.25

Table 12: Score Value for S_k^1

S_1	M1	M2	M3	M4
J1	**0.26**	0.12	0.12	0.076
J2	0.156	0.284	0.348	**0.484**
J3	**0.32**	0.19	0.085	0.048
J4	**0.404**	0.24	0.056	0.02

Table 13: Score Value for S_k^2

S_2	M1	M2	M3	M4
J1	**0.01**	-0.15	-0.175	-0.24
J2	-0.08	0.03	0.085	**0.19**
J3	**0.07**	-0.1	-0.175	-0.23
J4	**0.16**	0	-0.22	-0.23

Table 14: Score Value for S_k^3

S_3	M1	M2	M3	M4
J1	0.02	0.15	0.25	**0.27**
J2	**-0.01**	-0.09	-0.13	-0.22
J3	0.14	**0.25**	0.1	0.14
J4	-0.13	0	**0.16**	0.14

Table 15: Score Value for S_k^4

S_4	M1	M2	M3	M4
J1	**-0.01**	-0.3	-0.425	-0.51
J2	-0.07	0.12	0.215	**0.41**
J3	**-0.07**	-0.35	-0.275	-0.37
J4	**0.29**	0	-0.38	-0.37

Table 16: Score value for S_k^5

S_5	M1	M2	M3	M4
J1	**-0.26**	-0.54	-0.66	-0.716
J2	-0.292	-0.13	-0.022	**0.204**
J3	**-0.32**	-0.58	-0.52	-0.592
J4	**0.04**	-0.24	-0.552	-0.484

Case III

Step 1 and Step 2 are same as Case I

When the input matrixes are given, perform the transformation operation $P \otimes Q$ to get the job assignment matrix T. It is calculated using max-max-min composition and is given in table 17.

Table 17: Job Assignment Matrix Using Max-Max-Min Composition

T	Machine1(M1)	Machine2(M2)	Machine3(M3)	Machine4(M4)
Job(J1)	(0.5,0.6,0.5)	(0.4,0.5,0.7)	(0.4,0.5,0.8)	(0.3,0.4,0.8)
Job(J2)	(0.3,0.4,0.4)	(0.5,0.6,0.4)	(0.6,0.7,0.4)	(0.7,0.8,0.3)
Job(J3)	(0.5,0.6,0.5)	(0.4,0.5,0.7)	(0.4,0.5,0.7)	(0.3,0.4,0.7)
Job(J4)	(0.5,0.6,0.2)	(0.4,0.5,0.4)	(0.2,0.3,0.6)	(0.1,0.2,0.5)

Score values for the table 17 is calculated in table 18-23 using definition 2.7 and 2.15.

Table 18: Score Value Using Defn 2.7

	M1	M2	M3	M4
J1	0.53	0.53	**0.57**	0.5
J2	0.37	0.5	0.57	**0.6**
J3	**0.53**	**0.53**	**0.53**	0.47
J4	**0.43**	**0.43**	0.37	0.27

Table 19: Score Value for S_k^1

S_1	M1	M2	M3	M4
J1	**0.2**	0.05	0.0	-0.02
J2	0.14	0.26	0.32	**0.46**
J3	**0.2**	0.05	0.05	0.02
J4	**0.38**	0.2	0.02	0.0

Table 20: Score Value for S_k^2

S_2	M1	M2	M3	M4
J1	**-0.05**	-0.2	-0.25	-0.3
J2	-0.1	0	0.05	**0.15**
J3	**-0.05**	-0.2	-0.2	-0.25
J4	**0.1**	-0.05	-0.25	-0.25

Table 21: Score Value for S_k^3

S_3	M1	M2	M3	M4
J1	-0.1	0.05	0.1	**0.15**
J2	**-0.05**	-0.15	-0.2	-0.3
J3	-0.1	0.05	0.05	**0.1**
J4	-0.25	-0.1	**0.1**	**0.1**

Table 22: Score Value for S_k^4

S_4	M1	M2	M3	M4
J1	**0.05**	-0.25	-0.35	-0.45
J2	-0.05	0.15	0.25	**0.45**
J3	**0.05**	-0.25	-0.25	-0.35
J4	**0.35**	0.05	-0.35	-0.35

Table 23: Score Value for S_k^5

S_5	M1	M2	M3	M4
J1	**-0.2**	-0.5	-0.6	-0.68
J2	-0.28	-0.1	0.02	**0.26**
J3	**-0.2**	-0.5	-0.5	-0.58
J4	**0.1**	-0.2	-0.54	-0.48

Case IV

Step 1 and Step 2 are same as Case I

When the input matrixes are given, perform the transformation operation $P \otimes Q$ to get the job assignment matrix T. It is calculated using max-min-max composition and is given in table 24.

Table 24: Job Assignment Matrix using Max-Min-Max Composition

T	Machine1(M1)	Machine2(M2)	Machine3(M3)	Machine4(M4)
Job(J1)	(0.5,0.4,0.7)	(0.4,0.6,0.6)	(0.4,0.7,0.6)	(0.3,0.7,0.5)
Job(J2)	(0.3,0.3,0.5)	(0.5,0.3,0.7)	(0.6,0.3,0.8)	(0.7,0.2,0.9)
Job(J3)	(0.5,0.4,0.7)	(0.4,0.6,0.6)	(0.4,0.6,0.6)	(0.3,0.6,0.5)
Job(J4)	(0.5,0.1,0.7)	(0.4,0.3,0.6)	(0.2,0.5,0.4)	(0.1,0.4,0.3)

Score values for the table 24 is calculated in table 25-30 using definition 2.7 and 2.15

Table 25: Score Value using Defn 2.7

	M1	M2	M3	M4
J1	0.53	0.53	**0.57**	0.5
J2	0.37	0.5	0.57	**0.6**
J3	**0.53**	**0.53**	**0.53**	0.47
J4	**0.43**	**0.43**	0.37	0.27

Table 26: Score Value for S_k^1

S_1	M1	M2	M3	M4
J1	**0.22**	0.04	-0.02	-0.05
J2	0.15	0.29	0.36	**0.52**
J3	**0.22**	0.04	0.04	0.0
J4	**0.43**	0.22	0.0	-0.02

Table 27: Score Value for S_k^2

S_2	M1	M2	M3	M4
J1	**-0.05**	-0.2	-0.25	-0.3
J2	-0.1	0.0	0.05	**0.15**
J3	**-0.05**	-0.2	-0.2	-0.25
J4	**0.1**	-0.05	-0.25	-0.25

Table 28: Score Value for S_k^3

S_3	M1	M2	M3	M4
J1	**0.2**	-0.1	-0.2	-0.3
J2	0.1	0.3	0.4	**0.6**
J3	**0.2**	-0.1	-0.1	-0.2
J4	**0.5**	0.2	-0.2	-0.2

Table 29: Score Value for S_k^4

S_4	M1	M2	M3	M4
J1	-0.25	-0.1	-0.05	**0**
J2	**-0.2**	-0.3	-0.35	-0.45
J3	-0.25	-0.1	-0.1	**-0.05**
J4	-0.4	-0.25	**-0.05**	**-0.05**

Table 30: Score Value for S_k^5

S_5	M1	M2	M3	M4
J1	-0.5	-0.36	-0.32	**-0.29**
J2	**-0.41**	-0.55	-0.62	-0.76
J3	-0.5	-0.36	-0.36	**-0.32**
J4	-0.65	-0.48	-0.3	**-0.26**

After calculating the score values for all the cases, the maximum values are highlighted. To compare the results maximum values for case I is shown in table 31, case II is shown in table 32, case III is shown in table 33, case IV is shown in table 34.

Table 31: Maximum Values for all the Scores in Max-Avg-Min Composition

Max-avg-min composition						
	$\frac{a+b+c}{3}$	$S_k^1 = T_k - F_k I_k$	$S_k^2 = T_k - \left(\frac{F_K + I_K}{2}\right)$	$S_k^3 = \left(\frac{T_K + F_K}{2}\right) - I_K$	$S_k^4 = \left(\frac{T_K + I_K}{2}\right) - F_K$	$S_k^5 = (T_K * I_K) - F_K$
J1	M3	M1	M1	M3,m4	M1	M1
J2	M4	M4	M4	M1,m2,m3	M4	M4
J3	M3	M1	M1	M2	M1	M1
J4	M2	M1	M1	M3	M1	M1

Table 32: Maximum Values for all the Scores in Max-Prod-Min Composition

Max-prod-min composition						
	$\frac{a+b+c}{3}$	$S_k^1 = T_k - F_k I_k$	$S_k^2 = T_k - \left(\frac{F_K + I_K}{2}\right)$	$S_k^3 = \left(\frac{T_K + F_K}{2}\right) - I_K$	$S_k^4 = \left(\frac{T_K + I_K}{2}\right) - F_K$	$S_k^5 = (T_K * I_K) - F_K$
J1	M3	M1	M1	M4	M1	M1
J2	M4	M4	M4	M1	M4	M4
J3	M3	M1	M1	M2	M1	M1
J4	M2	M1	M1	M3	M1	M1

Table 33: Maximum Values for all the Scores in Max-Max-Min Composition

Max-max-min composition						
	$\frac{a+b+c}{3}$	$S_k^1 = T_k - F_k I_k$	$S_k^2 = T_k - \left(\frac{F_K + I_K}{2}\right)$	$S_k^3 = \left(\frac{T_K + F_K}{2}\right) - I_K$	$S_k^4 = \left(\frac{T_K + I_K}{2}\right) - F_K$	$S_k^5 = (T_K * I_K) - F_K$
J1	**M3**	M1	M1	M4	M1	M1
J2	M4	M4	M4	M1	M4	M4
J3	M1,M2,M3	M1	M1	M4	M1	M1
J4	**M1,M2**	M1	M1	M1,m3	M1	M1

Table 34: Maximum Values for all the Scores in Max-Min-Max Composition

Max-min-max composition						
	$\frac{a+b+c}{3}$	$S_k^1 = T_k - F_k I_k$	$S_k^2 = T_k - \left(\frac{F_K + I_K}{2}\right)$	$S_k^3 = \left(\frac{T_K + F_K}{2}\right) - I_K$	$S_k^4 = \left(\frac{T_K + I_K}{2}\right) - F_K$	$S_k^5 = (T_K * I_K) - F_K$
J1	M3	M1	M1	M1	M4	M4
J2	M4	M4	M4	M4	M1	M1
J3	M1,M2,M3	M1	M1	M1	M4	M4
J4	M1,M2	M1	M1	M1	M3,m4	M4

Defuzzification and all the scores except S_3 are same in table 31 and table 32. So both case I and case II will give the exact result. Similarly in table 33 defuzzification and S_3 is different from case I and case II but case III and case IV are same except the scores S_3, S_4, S_5. From the above tables 31,32,33and 34, it is clear that majority vote is allocated for Job 1

to machine 1, job 2 to machine 4, job 3 and job 4 it is machine 1. Also from these four compositions we obtain the same result which is used for the best decision.

5. CONCLUSIONS

To deal with uncertain, vague objects Molodtsov [5] originated the soft set theory as a general mathematical tool. In this paper, Sanchez's approach [10] for medical diagnosis is studied and the concept is applied by triangular fuzzy soft set theory. The results obtained from max-avg-min composition, max-prod-min composition, max-max-min composition, max-min-max composition are same based on the higher score value in the score function. Therefore fuzzy soft relation plays a major role in decision making which is efficient in practical life situation.

6. REFERENCES

1. *Chetia.B, Das.P.K., "An application of Interval-valued fuzzy soft sets in medical diagnosis",International Journal Contemp. Math. Sciences,Volume 5, (38), 1887-1894, 2010.*
2. *Degang chen, Tsang.E.C.C and Daniel S. Yeung, Xizhao wang.,"The parameterization reduction of soft sets and its applications", Computers and mathematics with applications, 49(757-763), 2005.*
3. *kalaiselvi.s and seenivasan.v., "Applications of fuzzy soft set in job scheduling problem', International journal for research in applied science & engineering technology, Volume 5, (3), 173-176, 2017.*
4. *Maji.P.K, R.Biswas, A.R. Roy, Fuzzy soft sets, The Journal of fuzzy mathematics 9(3) (2001) 589-602.*
5. *Molodtsov.D, The Theory of Soft Sets, URSS publishers, Moscow, 2004 (in Russian)*
6. *Muhammad irfan Ali, Feng Feng, Xiaoyan Liu,Won Keun Min, M.Shabir, On some new operations in soft set theory, Computers & Mathematics with Applications 57(9)(2009) 1547-1553.*
7. *Muhammad irfan Ali, 'A note on soft sets, rough soft sets and fuzzy soft sets', Applied soft computing (2011)*
8. *Palash dutta, Bulendra limbo,"Bell-shaped fuzzy soft sets and their application in medical diagnosis", Fuzzy Information and Engineering. 9,67-91,2017.*
9. *Saikia.B.K, Das.P.K and Borkakati.A.K, "An application of intuitionistic fuzzy soft sets in medical diagnosis", Bio science research bulletin, 19(2), 121-127, 2003.*
10. *Sanchez. E, Resolution of composite fuzzy relation equations, Information and control, 30,38-48, (1976).*
11. *Smarandache.F, "Neutrosophy and Neutrosophic logic, First international conference on Neutrosophy, Neutrosophic logic, set, probability and statistics", University of new mexico, gallup, NM87301, USA(2002).*
12. *Smarandache.F, "Neutrosophic set, a generalization of the intuitionistic fuzzy sets", International journal of pure and applied mathematics.,24,287-297,2005.*
13. *Yildiray celik, "A model for medical diagnosis via fuzzy neutrosophic soft sets", Asian journal of mathematics and computer research 10(1) : 60-68, 2016.*
14. *Yildiray celik, ilknur celik., "A framework for medical diagnosis via fuzzy soft matrices", New trends in mathematical sciences, Volume 2, 248-256, 2016.*
15. *Yuncheng Jiang, Yong Tang, Qimai chen, "An adjustable approach to intuitionistic fuzzy sets based decision making", Applied Mathematical Modelling 35(2)(2011) 824-836.*

16. Zhi Kong, Liqun Gao, Lifu Wang, Comment on "A fuzzy soft set theoretic approach to decision making problems", Journal of computational and applied mathematics 223(2)(2009) 540-542.